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AI-Assisted Oral Imaging Diagnosis in Clinical Applications of Dentistry: A Review

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Abstract: Artificial intelligence (AI), particularly deep learning and convolutional neural networks (CNNs), is increasingly used in dental and maxillofacial imaging for classification, detection, segmentation, and quantitative assessment. Applications include dental caries, periodontal bone loss, jaw lesions, orthodontic measurements, and impacted-tooth localization. This narrative review emphasizes the technical foundations of AI-assisted oral imaging, including CNN architectures, preprocessing, annotation, augmentation, evaluation, and external validation, while summarizing representative clinical applications. Current studies report promising performance in selected tasks, but generalizability is constrained by heterogeneous datasets, imaging protocols, annotation standards, and limited multicenter validation. Clinical translation further requires explainability, workflow integration, regulatory oversight, and prospective evaluation.

Keywords: Artificial intelligence; Oral imaging; Diagnosis; Deep learning; Dental caries; Periodontal disease; CBCT

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1. Introduction

Oral imaging, including panoramic and periapical radiography and cone-beam computed tomography (CBCT), is central to evaluating teeth, periodontal tissues, jawbones, and related structures. Conventional interpretation depends substantially on clinician experience and may be affected by subtle radiographic findings, anatomical overlap, image quality, and interobserver variability. AI-assisted image analysis has therefore been investigated as an adjunct for improving consistency and efficiency.

Deep-learning systems can learn image features directly from data and perform classification, detection, and segmentation. In dentistry, AI has been investigated for tooth classification in CBCT, jaw-tumor detection, periodontal bone-loss assessment, impacted-tooth localization, and other imaging tasks [1–5]. Nevertheless, reported performance varies with the clinical task, dataset, imaging modality, reference standard, and validation design. Much of the evidence remains retrospective, and external validation, prospective workflow evaluation, and patient-relevant outcomes are limited [6].

2. AI-assisted oral imaging diagnosis: Technical foundations

2.1. Deep learning and convolutional neural networks

Deep learning relies on multilayer neural networks that derive progressively more abstract representations from raw data. This property is particularly useful in imaging, where convolutional layers capture local spatial patterns, pooling operations compress feature maps, and deeper layers combine these patterns for classification or regression. In oral radiology, the resulting representations may reflect tooth morphology, trabecular texture, or differences in lesion density, without requiring these features to be specified in advance.

The same framework can be adapted to several distinct imaging tasks. Classification assigns an image or region to a diagnostic category, whereas detection identifies the location of a tooth or lesion. Segmentation is more granular because it defines anatomical or pathological structures at the pixel or voxel level. ResNet- and U-Net-based models are frequently adapted through transfer learning when task-specific annotations are limited. Even so, prior training does not, by itself, ensure stable performance after a model is moved to another clinical setting.

Published applications illustrate this range of functions. Intraoral photographs have been used for automated recognition of posterior restorations and fissure sealants [7,8]. In CBCT, CNNs have been investigated for scatter correction and image enhancement, while segmentation methods have also been applied to calcified carotid artery atheromas [9,10]. Taken together, these examples show that an AI-assisted diagnostic workflow may incorporate several linked operations rather than a single predictive step.

2.2. Data preprocessing and annotation strategies

Input quality places an early constraint on model performance. Dental images differ across devices and exposure settings, and they are also affected by positioning, anatomy, motion, and metal-related artifacts. Preprocessing is intended to reduce some of this unwanted variation through procedures such as intensity normalization, contrast adjustment, artifact suppression, and registration. For CBCT specifically, CNN-based scatter correction has been explored as a means of reducing noise while preserving image fidelity [9].

Reliable supervision is equally important. Expert annotations are commonly treated as the reference standard, although disagreement between examiners and uncertainty at lesion margins can be carried into both training and evaluation. Semi-automated labeling and active-learning strategies may ease this burden by directing expert attention toward cases for which the model is least certain, rather than requiring every image to be annotated with the same level of manual effort.

Augmentation is often used to broaden the apparent variation within a training set, for example through rotation, cropping, deformation, or changes in intensity. These transformations may lessen class imbalance and reduce overfitting, but they remain derivatives of the original data. They cannot establish transportability. That question must be addressed with independent images obtained from other populations, devices, institutions, and acquisition conditions.

2.3. Model evaluation, external validation, and clinical utility

Evaluation begins with a clear match between the intended clinical task and the reference standard. Depending on the condition under study, an appropriate standard may be histopathology, expert consensus, or longitudinal clinical outcome. The unit of analysis also matters: results reported per tooth, lesion, image, or patient answer different questions and should not be compared as though they were equivalent. For segmentation, overlap statistics are informative but should be accompanied by clinically meaningful boundary or surface-error measures when those errors could affect interpretation or treatment planning.

Internal test performance, external validity, and clinical usefulness should therefore be reported separately. Classification and detection studies commonly present sensitivity, specificity, predictive values, accuracy, and the area under the receiver operating characteristic curve. Segmentation studies require additional spatial-overlap or surface-distance measures. No single metric is sufficient in every setting; interpretation depends on disease prevalence, the chosen unit of analysis, the purpose of the system, and the relative consequences of false-positive and false-negative findings.

Caries detection provides a useful example. Although several studies have reported favorable discrimination with CNNs, the estimates vary with dataset composition, lesion definition, imaging modality, and the reference standard used [11]. A model that performs well after an internal data split may behave differently when exposed to images from another clinic. External testing across centers, devices, and patient populations is therefore a prerequisite for judging generalizability, and prospective studies are still needed to determine how model use changes workflow and clinical outcomes.

The value of AI also depends on how clinicians interact with its output. In a randomized study of periapical radiolucency detection, AI support produced a modest improvement in dentists' overall diagnostic accuracy, largely through fewer false-positive decisions; this result should not be extrapolated to unrelated dental tasks [12]. Methods such as gradient-weighted class activation mapping (Grad-CAM) can indicate which image regions contributed to a prediction and may support review or error analysis [13]. Such displays are helpful only as part of a broader clinical assessment that also considers speed, reproducibility, safety, compatibility with existing workflow, and evidence of meaningful benefit.

3. Specific applications of AI in oral imaging

3.1. Caries and apical lesions

Radiographic caries detection is among the most frequently studied dental applications of CNNs. Systematic reviews generally describe encouraging diagnostic performance, but sensitivity and specificity differ considerably across studies and imaging modalities [14]. Similar methods have been evaluated for periapical and cyst-like radiolucencies on panoramic radiographs and CBCT images [15]. These outputs may assist lesion recognition and measurement, yet imaging features alone do not always distinguish pathology definitively. Clinical examination and histopathology when indicated, therefore, remain necessary, while evidence that these systems improve patient-level outcomes is still limited [16–18].

3.2. Periodontal disease

For periodontal assessment, deep-learning methods have been applied mainly to alveolar bone levels and related radiographic features [19]. Automated measurement may improve consistency between operators, but reported endpoints are not interchangeable: bone-level estimation, furcation assessment, and disease classification represent different tasks. Periodontal pocket depth is determined clinically and cannot be read directly from a radiograph. Robust use will consequently depend on training data that capture relevant population diversity and on imaging protocols that are sufficiently standardized for reproducible measurement.

3.3. Oral and maxillofacial tumors and cysts

Odontogenic tumors and cyst-like lesions have been investigated with both classification and segmentation models [20]. Segmentation is potentially useful for volumetric assessment and for describing lesion extent, whereas classification addresses a different diagnostic question. AI has also been studied in oral-cancer imaging and histopathology, although the available literature spans different modalities and does not support a single overall estimate of diagnostic performance [17,21]. Small annotated datasets, variable acquisition protocols, and limited external validation continue to restrict the strength of the evidence.

3.4. Orthodontic measurement and impacted teeth

Orthodontic applications include automated identification of cephalometric landmarks, calculation of measurements, and localization of impacted teeth [18,22]. On panoramic radiographs and CBCT, algorithms may help define tooth position and its relationship to adjacent anatomical structures, information that can be relevant to treatment or surgical planning. Before such tools are used routinely, their performance needs to be examined across anatomical variation, imaging devices, and clinical environments rather than only under the conditions in which they were developed.

4. Challenges and future directions

4.1. Standardization, generalizability, and reproducibility

Generalizability is particularly difficult in oral imaging because image appearance changes with scanner design, exposure settings, reconstruction parameters, patient positioning, and local acquisition practice. A model trained on carefully selected images from one institution may therefore lose accuracy when used elsewhere. Larger public datasets and multicenter collaboration can improve diversity, but sample size is only one part of the problem. Consistent annotation, transparent reporting, representative case selection, and genuinely independent testing need to be incorporated into model development from the outset.

Variation in scanner type, resolution, exposure, reconstruction, patient population, and labeling protocol produces domain shifts that may only become apparent during external testing. Rare disorders add a separate difficulty because available datasets are often both small and imbalanced. Multicenter repositories, harmonized annotation procedures, detailed reporting, and validation across several devices should therefore be treated as priorities rather than optional extensions [23,24].

Federated learning offers one route for institutions to collaborate without transferring raw patient images between sites. Synthetic data may also increase the representation of uncommon classes, but generated images require careful evaluation and cannot replace testing in representative clinical populations. Ultimately, reproducibility is demonstrated by independent performance across settings in which the system is expected to be used, not by repeated analysis of variations derived from the same source dataset.

4.2. Clinical integration, regulation, and ethics

Clinical deployment requires more than an accurate algorithm. AI output must be incorporated into dental information systems in a form that can be reviewed without disrupting routine interpretation. Heatmaps, confidence estimates, and quantitative overlays may help clinicians judge a result, but they do not remove the need for professional oversight. Systems intended for patient care must also undergo appropriate medical-device evaluation, with evidence addressing safety, efficacy, and consistency under the conditions of use.

Privacy, data security, bias, and responsibility for error remain central concerns during both development and deployment. Compliance with applicable data-protection requirements should be accompanied by clear communication of model limitations and foreseeable failure modes. Safe implementation will therefore require sustained collaboration among dental clinicians, AI developers, regulators, legal specialists, and other stakeholders rather than decisions made by a single professional group [25,26].

4.3. Multimodal models and clinical decision support

Combining images with other forms of patient information creates additional methodological problems. Clinical history, radiographic features, and molecular data differ in scale, completeness, and dimensionality, and a multimodal model should be shown to add value beyond a simpler alternative. Models designed to predict treatment-related outcomes also require task-specific validation; diagnostic accuracy cannot be assumed to translate into reliable prognostic performance. Explainability tools may support error analysis by highlighting influential image regions, but their clinical contribution needs to be tested rather than presumed. Future decision-support studies should therefore evaluate calibration, external validity, workflow fit, and prospective performance alongside conventional accuracy measures.

Future systems may integrate radiographic findings with medical history, systemic conditions, and molecular or other patient-level data. In principle, this could refine disease characterization or risk stratification. The relevant comparison, however, is not an imaging-only model in isolation but the best available conventional clinical approach. Any claimed benefit must be demonstrated empirically, and strong diagnostic discrimination should not be interpreted automatically as evidence of accurate treatment-outcome prediction.

Attention maps and Grad-CAM can show image regions associated with a model's output, but they do not provide a complete account of the reasoning that produced the prediction. Research should accordingly place greater emphasis on calibration, external testing, prospective evaluation, failure analysis, and outcomes that matter in clinical practice, rather than treating high accuracy on a retrospective dataset as the final objective [27,28].

Preprocessing and annotation are closely linked because both shape the information presented to the learning algorithm. Differences in contrast, noise, artifacts, or anatomical presentation can alter feature extraction, while inconsistent labels introduce uncertainty into supervised training. Augmentation may enlarge the training set through rotation, cropping, deformation, or intensity adjustment, yet each transformed image still originates from the same underlying data. Independent testing across other populations, devices, and clinical settings is therefore needed to assess transportability.

Clinical implementation also depends on computational efficiency and interoperability. Even a technically accurate system has limited practical value when processing is too slow or when its output cannot be incorporated into established imaging software. Visual explanations, confidence information, and reproducible measurements may support clinical review, but they remain aids to professional judgment. Prospective studies should examine interpretation time, error patterns, treatment decisions, and patient-relevant outcomes in addition to diagnostic metrics.

Viewed as a whole, oral-imaging AI is a chain of dependent stages. Acquisition and preprocessing influence input consistency; expert annotation defines the target; model architecture determines how features are learned and predictions are produced; validation tests performance and generalizability; and integration determines whether those predictions can be used safely. A weakness at any point can limit the value of the complete system. Transparent reporting across this sequence is necessary if results are to be reproduced and compared between institutions.

5. Conclusion

AI-assisted oral imaging has demonstrated promising performance in classification, detection, segmentation, and quantitative assessment across caries, periodontal disease, jaw lesions, and orthodontic applications. Its principal technical strengths arise from deep-learning methods capable of extracting complex imaging features and automating image-analysis tasks.

However, high internal accuracy alone is insufficient for clinical adoption. Dataset heterogeneity, annotation quality, domain shift, limited external validation, explainability, workflow integration, privacy, and regulation remain substantial challenges. Future research should prioritize standardized multicenter datasets, transparent reporting, independent and prospective validation, and evaluation of human–AI workflows. Multimodal and explainable systems may extend clinical decision support, but their value must be demonstrated through reproducible and clinically relevant evidence.

Disclosure statement

The author declares no conflict of interest.

References

[1] Miki Y, Muramatsu C, Hayashi T, et al., 2017, Classification of Teeth in Cone-Beam CT Using Deep Convolutional Neural Network. Computers in Biology and Medicine, 80: 24–29.

[2] Poedjiastoeti W, Suebnukarn S, 2018, Application of Convolutional Neural Network in the Diagnosis of Jaw Tumors. Healthcare Informatics Research, 24(3): 236–241.

[3] Kim J, Lee H, Song I, et al., 2019, DeNTNet: Deep Neural Transfer Network for the Detection of Periodontal Bone Loss Using Panoramic Dental Radiographs. Scientific Reports, 9(1): 17615.

[4] Orhan K, Bilgir E, Bayrakdar I, et al., 2021, Evaluation of Artificial Intelligence for Detecting Impacted Third Molars on Cone-Beam Computed Tomography Scans. Journal of Stomatology, Oral and Maxillofacial Surgery, 122(4): 333–337.

[5] Başaran M, Çelik Ö, Bayrakdar I, et al., 2022, Diagnostic Charting of Panoramic Radiography Using Deep-Learning Artificial Intelligence System. Oral Radiology, 38(3): 363–369.

[6] Ardila C, Vivares-Builes A, Pineda-Vélez E, 2026, From Algorithmic Performance to Clinical Translation: Translational Readiness of Imaging-Based Artificial Intelligence in Dentistry—A Systematic Review. Healthcare, 14(13): 1952.

[7] Engels P, Meyer O, Schönewolf J, et al., 2022, Automated Detection of Posterior Restorations in Permanent Teeth Using Artificial Intelligence on Intraoral Photographs. Journal of Dentistry, 121: 104124.

[8] Schlickenrieder A, Meyer O, Schönewolf J, et al., 2021, Automatized Detection and Categorization of Fissure Sealants From Intraoral Digital Photographs Using Artificial Intelligence. Diagnostics, 11(9): 1608.

[9] Nomura Y, Xu Q, Shirato H, et al., 2019, Projection-Domain Scatter Correction for Cone Beam Computed Tomography Using a Residual Convolutional Neural Network. Medical Physics, 46(7): 3142–3155.

[10] Alajaji S, Amarin R, Masri R, et al., 2024, Detection of Extracranial and Intracranial Calcified Carotid Artery

Atheromas in Cone Beam Computed Tomography Using a Deep Learning Convolutional Neural Network Image Segmentation Approach. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology, 138(1): 162–172.

[11] Lee J, Kim D, Jeong S, et al., 2018, Detection and Diagnosis of Dental Caries Using a Deep Learning-Based Convolutional Neural Network Algorithm. Journal of Dentistry, 77: 106–111.

[12] Pul U, Tichy A, Pitchika V, et al., 2025, Impact of Artificial Intelligence Assistance on Diagnosing Periapical Radiolucencies: A Randomized Controlled Trial. Journal of Dentistry, 160: 105868.

[13] Görürgöz C, Orhan K, Bayrakdar I, et al., 2022, Performance of a Convolutional Neural Network Algorithm for Tooth Detection and Numbering on Periapical Radiographs. Dentomaxillofacial Radiology, 51(3): 20210246.

[14] Albano D, Galiano V, Basile M, et al., 2024, Artificial Intelligence for Radiographic Imaging Detection of Caries Lesions: A Systematic Review. BMC Oral Health, 24(1): 274.

[15] Naeimi S, Darvish S, Salman B, et al., 2024, Artificial Intelligence in Adult and Pediatric Dentistry: A Narrative Review. Bioengineering, 11(5): 431.

[16] Kühnisch J, Meyer O, Hesenius M, et al., 2022, Caries Detection on Intraoral Images Using Artificial Intelligence. Journal of Dental Research, 101(2): 158–165.

[17] Sukegawa S, Ono S, Tanaka F, et al., 2023, Effectiveness of Deep Learning Classifiers in Histopathological Diagnosis of Oral Squamous Cell Carcinoma by Pathologists. Scientific Reports, 13(1): 11676.

[18] Zhu J, Chen Z, Zhao J, et al., 2023, Artificial Intelligence in the Diagnosis of Dental Diseases on Panoramic Radiographs: A Preliminary Study. BMC Oral Health, 23(1): 358.

[19] Roy R, Chopra A, Karmakar S, et al., 2025, Applications of Artificial Intelligence (AI) for Diagnosis of Periodontal/Peri-Implant Diseases: A Narrative Review. Journal of Oral Rehabilitation, 52(8): 1193–1219.

[20] Giraldo-Roldán D, Nakamura T, Claret A, et al., 2026, Impact of Transfer Learning on Convolutional Neural Networks for Odontogenic Tumor Diagnosis. Head and Neck Pathology, 20(1): 24.

[21] Kamat M, Datar U, Kumar V, 2025, Insights Into AI-Enabled Early Diagnosis of Oral Cancer: A Scoping Review. Cureus, 17(7): e88407.

[22] Makaremi M, Sadr A, Marcy B, et al., 2023, An Interpretable Machine Learning Approach to Study the Relationship Between Retrognathia and Skull Anatomy. Scientific Reports, 13(1): 18130.

[23] Mureșanu S, Almășan O, Hedeșiu M, et al., 2023, Artificial Intelligence Models for Clinical Usage in Dentistry with a Focus on Dentomaxillofacial CBCT: A Systematic Review. Oral Radiology, 39(1): 18–40.

[24] Alahmari M, Alahmari M, Almuaddi A, et al., 2025, Accuracy of Artificial Intelligence-Based Segmentation in Maxillofacial Structures: A Systematic Review. BMC Oral Health, 25(1): 350.

[25] Ahmed N, Abbasi M, Zuberi F, et al., 2021, Artificial Intelligence Techniques: Analysis, Application, and Outcome in Dentistry—A Systematic Review. BioMed Research International, 2021: 9751564.

[26] Chen R, Lee Y, Li J, 2026, The Science Behind Machine Learning, Deep Learning, and Active Learning. Dental Clinics of North America, 70(2): 351–359.

[27] Syed A, Ozen D, Duman S, et al., 2026, Radiographic Data Segmentation as a Tool in Machine Learning and Deep Learning Artificial Intelligence Algorithms. Dental Clinics of North America, 70(2): 331–349.

[28] Mathur A, Mehta V, Bhadania M, et al., 2026, Artificial Intelligence in Dental Implant Identifications, Planning Accuracies, and Success Predictions: An Umbrella Review. The Journal of Prosthetic Dentistry, 136(2): 412–421.